

# HIGGS SEARCH BY NEURAL NETWORKS AT LHC

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## ABSTRACT

We show that neural network classifiers can be used to discriminate Higgs production from background at LHC for  $150 < M_H < 200$  GeV. The results compare favourably with ordinary multivariate analysis.

# 1 Introduction

Experimental data accumulated so far, and especially the LEP results, strongly support the Standard Model (hereafter denoted as SM) as the theory of the fundamental interactions at the presently available energies. Nevertheless the verification of its validity has to be completed since the top quark and Higgs boson have not been discovered yet.

As well known, the value of the Higgs mass is not predictable, but there are indications, arising from the limits of applicability of the perturbation theory or violation of unitarity, that it should not exceed 800 GeV [1]. If Higgs particles below  $\approx 1$  TeV are not discovered, other strong forces could be at work, as predicted by the Technicolor [2] scheme, which however, at least in its minimal version, is not favored by LEP data [3]; in this and other similar approaches the strongly interacting scalar sector might be revealed by the presence of new vector bosons [4] and some light on the electroweak symmetry breaking could be shed by longitudinal boson scattering. Another theoretical extension of SM is provided by Supersymmetry (SUSY) (for reviews see[5]), which, as well known, naturally solves the *hierarchy problem* because boson and fermion loops contributions to scalar masses have opposite signs in SUSY and tend to cancel out, thus avoiding Higgs masses of the order of the Grand Unification scale  $M_{GUT} \sim 10^{16}$  GeV. In the sequel, however, we shall consider only the SM Higgs also because its search is the first motivation for the future high energy hadron colliders, and also since one of the SUSY Higgs particles exhibits a similar behaviour.

The present upper limit on the SM Higgs mass coming from LEP is 63 GeV [6]. Therefore, since the LEP 200 discovery limit is around 80 – 90 GeV, more energetic colliders are mandatory to pin down the mechanism of the electroweak symmetry breaking.

In this letter we will consider experiments aiming to discover the SM Higgs at the future Large Hadron Collider (LHC) which is planned for the end of this century at CERN. Within the Standard Model the discovery of the Higgs particle should be complicated by the presence of huge backgrounds. Considerable effort has been provided by the Aachen workshop of the LHC study groups to clarify this issue, and we refer the interested reader to the Proceedings [7] of that Conference for a comprehensive survey. Our aim here is to analyze the possibility to use a neural network (NN) classifier as a tool for a better discrimination between signal and background and to evaluate the relative performance between the neural trigger and traditional statistical methods such as the multivariate analysis. Given the limits of the present work we shall not consider the whole Higgs mass range nor we study all the possible Higgs decay channels, but we shall limit ourselves to some specific case studies. More precisely we shall analyze the Higgs mass range 150 – 200 GeV and study the decay into four muons, which, as shown by the above mentioned LHC study groups, seems to be the most favourable decay channel for Higgs discovery.

We first discuss in section 2 a possible choice of the physical observables useful for the separation of the Higgs signal from background; these observables are the input variables for the NN classifier that is described in the same section. We present our results and discuss the relative performance of the NN method and multivariate analysis in section 3. Finally, in section 4 we draw our conclusions.

## 2 Physical observables and the neural network

At hadron colliders the dominant mechanism for Higgs production, in the intermediate mass range we are interested in, is gluon-gluon fusion. The best decay channel for identification is two real  $Z^0$  bosons for Higgs mass  $M_H \geq 2M_Z$  or, for  $M_H \leq 2M_Z$ , one real and one off-shell  $Z^0$ , followed by their leptonic decays. LHC studies have shown that this channel is the most efficient one for  $130 \leq M_H \leq 800$  GeV; we shall consider here the case  $M_H = 150$  GeV where the presence of one virtual  $Z^0$  renders the analysis more demanding and the case  $M_H = 200$  GeV just above the threshold for production of two real  $Z$ 's. In this region the top production comprises the most important background. Usual ways to reduce the background are lepton isolation, lepton pair mass constraints around  $Z$  mass and a lepton detection threshold around  $P_T^\ell \simeq 10$  GeV [7]. In this paper we do not impose any cut on physical variables, but we simply choose a set of physical observables whose values represent the entries of a neural classifier, since we expect that, by an appropriate choice of such observables, the discrimination should automatically occur as a result of the neural classifier.

Before discussing the variables let us examine the background in more detail. Besides  $t\bar{t}$  production followed by top semileptonic decay to bottom and  $b$  semileptonic decay, one expects other sources of background, most notably  $Zb\bar{b}$ ; however, as shown by the LHC study groups, this process is expected to contribute by around only one third of  $t\bar{t} \rightarrow 4\mu$  to the cross section; therefore we shall neglect it at this stage because in this letter we are more interested in a study of the relative performance of the NN and the multivariate analysis rather than a comprehensive study of the background. In any event we do not expect a significant change of the results, should these other minor backgrounds be included.

On the other hand several other background processes become important if one does not impose cuts on lepton transverse momenta; to take into account them, together with the dominant  $t\bar{t} \rightarrow 4\mu X$ , we shall include as background processes all the events where four muons are in the final state and a  $t\bar{t}$  pair has been produced, without forcing their decay. We have checked, by simulating the events by the Pythia Montecarlo[8], that these background events produce  $\sigma \times BR \simeq 11 pb$ , which is larger by a factor of about 25 as compared to  $\sigma \times BR$  for  $pp \rightarrow t\bar{t}X \rightarrow 4\mu X$ , choosing a top mass of 130 GeV [9].

Let us now list the physical observables we have used for discrimination between background and signal. We have considered 10 observables, that are:

$X_1$ ) -  $X_4$ ) the transverse momentum of the four muons. The two  $\mu^+$  and the two  $\mu^-$  can be ordered according to their energies. As expected, the distributions of these variables for background events, as simulated by the Pythia Montecarlo, show a maximum close to zero, while the signal distributions show a peak around 25 – 50 GeV,

$X_5$ ) -  $X_8$ ) The invariant masses of the four different  $\mu^+\mu^-$  pairs. Also these pairs can be ordered according to the lepton energies. These distributions for signal events show a peak around the  $Z^0$  mass which are absent for the background. The peaks arise from events where two muons come from the real  $Z^0$ ; they are present in all the 4 variables since the ordering based on the energy mixes in part the muons coming from the two  $Z^0$ ,

$X_9$ ) The four muons invariant mass,

$X_{10}$ ) The hadron multiplicity.

This choice of variables is mainly based on kinematical considerations and should be considered as *minimal*, since we expect that other dynamical variables, besides the hadron multiplicity, can improve the performance of the network. We shall come back to this point later on.

The physical observables  $X_j$  discussed above, once normalized to the interval  $[0 - 1]$ , become the inputs  $x_j$  ( $j = 1, \dots, n$ ) of our neural network classifier. We employ the most common architecture used for high energy applications (see, e.g. [10]), i.e. the *feed-forward* neural network; in our case it comprises one input layer with  $n = 10$  neurons  $x_j$ , one layer with  $2n + 1$  hidden neurons  $z_j$  and one output unit  $y$ . We employ the *backpropagation* algorithm [11] to train the network. The events are divided into two sets, the training and the testing set. Each event  $p$  of the training set consists of the array  $x_j$  of the input variables and the value  $y$  of the output neuron ( $y = 0$  or  $1$  for the event describing the signal, i.e. Higgs production, or the background, respectively). At each time step and for any pattern  $p$  in the training set, the algorithm modifies the synaptic couplings giving the strength of the interaction between the hidden layer and the output neuron:

$$W_i \rightarrow W_i + \Delta W_i^{(p)} \quad (2.1)$$

with

$$\Delta W_i^{(p)} = -\lambda \frac{\partial E^{(p)}}{\partial W_i} + \alpha \Delta W_i^{(old)}, \quad (2.2)$$

where

$$E^{(p)} = \frac{1}{2}(y^{(p)} - t^{(p)})^2 \quad (2.3)$$

In the previous equation, for any pattern  $p$  in the training set,  $t^{(p)}$  is the expected *target* ( $t^{(p)} = 0$  or  $1$ , for signal and background event respectively) and  $y$  is given by:

$$y = g(u, \theta) \quad (2.4)$$

where the transfer function  $g(u, \theta)$  is as follows:

$$g(u, \theta) = \frac{1}{1 + \exp(-\frac{u-\theta}{T})} \quad (2.5)$$

and  $u$  is given in terms of the hidden variables by  $u = \sum_{l=1}^{2n+1} W_l z_l$ . Similar relations hold among the hidden variables  $z_k$  and the input neurons  $x_j$ , so that the repeated application of Eqs. (2.1) and (2.2) fixes the couplings  $W_{lk}$  between the hidden neurons  $z_k$  and the input neurons  $x_l$  as well. In our simulations we use the values  $\alpha = 0.9$ ,  $\lambda = 1$  and  $T = 1$  for the network parameters.

### 3 Results

Our simulations have been obtained by the Pythia Montecarlo Code [8]. We have considered two masses of the Higgs particle: one below  $2M_Z$  i.e. 150 GeV, and one just above, i.e. 200 GeV. The top quark mass has been put equal to 130 GeV (increasing  $m_t$  improves the results since it reduces the background). The simulated events have been divided into two sets, the training set, used by the network to learn, and the testing set, used to test the performance of the NN. The training set consists of an equal number  $N = 5,000$  of background and signal events: we have checked that the results are stable against changes of  $N$ . On the other hand in the testing set the populations of the two samples, background and signal, have been taken different; as a matter of fact, we have considered 2,000 signal  $pp \rightarrow HX \rightarrow 4\mu X$  events, independently of the Higgs mass, while one has to take  $1.1 \times 10^7$  and  $4.3 \times 10^6$  background events for the two cases of  $M_H = 150$  and 200 GeV respectively. The ratios between signal and background cross section that we use are computed in the Standard Model by the Pythia Montecarlo.

If the sample is statistically significant one may consider a smaller set of background events and rescale the final results (i.e. the number of misinterpreted background events) according to the predictions of the Standard Model. We have checked that this procedure works already with 50,000 background events.

We have considered four different cases in our simulations. In the first case the 10 variables have been used with no cuts; the number of simulated events quoted above refers to this case. In the second case, in order to increase the ratio signal/background, we have considered only muons with the  $4\mu$  invariant mass in the range  $M_H \pm 10$  GeV. In these simulations we have obtained slightly worse results, i.e. the discrimination seems more difficult; moreover, in this case, the training phase lasts longer.

In order to determine the most suitable variables for this kind of study, we have also repeated the analysis by using only five variables. We have considered two of these cases, one with  $x_1, x_2, x_3, x_4$  and  $x_9$  as input variables and the other with input variables  $x_5, x_6, x_7, x_8$ , and  $x_9$ . In both these cases the results are slightly worse as compared to the choice of 10 variables. Therefore, in the evaluation of the performance of the NN we shall refer to the first of the four cases we have discussed, i.e. 10 variables with no cut on  $M_{\mu\mu\mu\mu}$ .

The performance of the NN classifier can be assessed by introducing two variables: the purity ( $P$ ) and the efficiency ( $\eta$ ) defined as follows:

$$P = \frac{N_H^a}{N_H^a + N_B^a} \quad (3.1)$$

and

$$\eta = \frac{N_H^a}{N_H} \quad (3.2)$$

where  $N_H$  is the total number of Higgs events in the testing sample,  $N_H^a$  is the total number of the accepted (i.e. correctly identified) Higgs events and  $N_B^a$  is the total number of the accepted background events, i.e. events that are incorrectly identified as Higgs events.

One can increase the purity decreasing the efficiency by introducing a threshold parameter  $l \in [0, 1]$  as follows. The range of values of the output neuron  $y^{(p)}$  in the testing

phase is divided into the subintervals:  $I_1 = [0, l]$  and  $I_2 = ]l, 1]$ , so that if  $y^{(p)} \epsilon I_1$  (respectively  $y^{(p)} \epsilon I_2$ ) the event is classified as signal (respectively: background). Clearly, by taking  $l$  sufficiently small, one increases purity. For example at  $M_H = 150$  GeV one obtains  $P = 0.1$  for  $l \approx 10^{-3}$  and  $P = 0.25$  for  $l \approx 0.5 \times 10^{-4}$ .

Our results are reported in Fig. 1, which shows that, as expected, the case with  $M_H = 200$  GeV is certainly more favourable than the case with  $M_H = 150$  GeV. Fig. 1 also shows that in both cases one can reach appreciable values of purity, even though, especially for low Higgs mass, the reduction of efficiency is relevant.

Let us now compare these results with the maximum likelihood method. First of all, as a general comment, we observe that the neural network is more flexible than the multivariate analysis, since in the former case by an appropriate choice of the parameter  $l$  one can increase the purity without limitations, at least in principle. This flexibility is absent in the multivariate analysis because this method only uses averages and not a uniform fit to the data as the NN does. When the comparison is possible, i.e. for values of the efficiency larger than 30%, the maximum likelihood method gives results that are significantly worse. By way of example, at  $M_H = 150$  GeV with an efficiency of 85% the traditional method gives a purity of 0.02 (a factor of 3 worse than the NN result of Fig. 1); with an efficiency of 99% the traditional method gives a purity of 0.01, again worse than NN. Similar results are obtained with  $M_H = 200$  GeV: for example, the efficiency of 34% corresponds, with the traditional method, to a purity of 0.07, while NN gives a purity of roughly 0.35 at the same value of efficiency.

## 4 Conclusions

Our results show that NN can be of some help in the difficult task of discriminating background events from the signal in the Higgs search at the future Large Hadron Collider to be built at CERN. We have proved this by considering one particular Higgs decay channel ( $H \rightarrow 4\mu$ ) in the Higgs mass range (150-200) GeV and including the most relevant background. We are conscious of the limits of the present analysis: for example other sources of background should be included and different Montecarlo's might be employed to test the independence of the results from the theoretical inputs. Moreover other global variables, similar to the hadron multiplicity and sensitive to the infrared structure of the QCD radiation could be introduced, even though the use of preprocessed observables might limit the whole range of possibilities of the neural trigger. We plan to perform these analysis in a subsequent paper. On the other hand, from our experience on a similar subject [12] we do not expect a dependence of the results on the architecture of the neural network. We feel, therefore, that we have correctly addressed the main point i.e. the comparison between the neural network and the usual multivariate analysis based on the maximum likelihood method. Our results show that NN compare favourably with the traditional statistical analysis. Needless to say that NN have another clear advantage over traditional statistical methods, since they can support a high degree of parallelism and could be used for on-line analysis of the experimental data. Therefore their use in the future LHC experiments should be seriously considered and thoroughly investigated.

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## Figure Caption

**Fig. 1** The purity  $P$  versus the Higgs efficiency  $\eta$  for two different sets of data:  $M_H = 150$  and  $200$  GeV (lower and upper line respectively).

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